A Vocal Learning Model: Development And Analysis

Silvia Pagliarini, Arthur Leblois, Xavier Hinaut

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AIM: build a vocal learning model underlying song learning in birds, and understand how to make it biologically plausible.

INTRODUCTION

KEYWORDS

Sensorimotor learning: control problem which maps a sensory input into a motor output.

Imitation: the ability to replicate another's behaviour, i.e. to generate an appropriate motor command to reproduce a sensory stimulus.

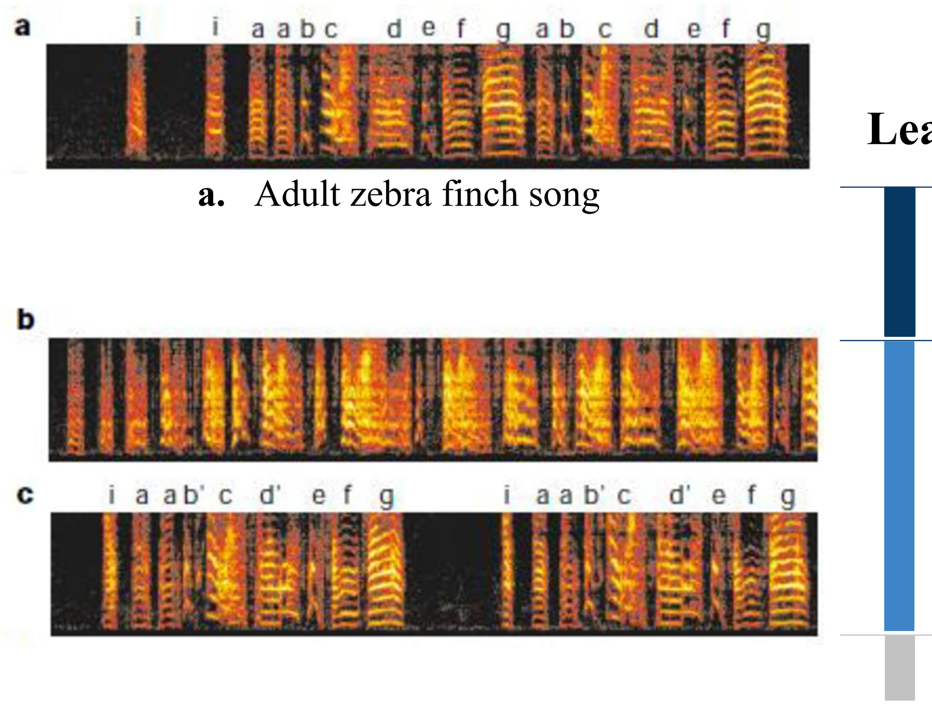
Inverse model learning: use the desired and actual motor configuration to estimate the motor commands needed to reach the desired configuration (to produce the appropriate sensory stimulus).

Reinforcement learning: learn an action policy to maximize the expected reward (which encode the goal of the learning).

Da Cunha et al.,2010

VOCAL LEARNING IN BIRDS

TUTOR



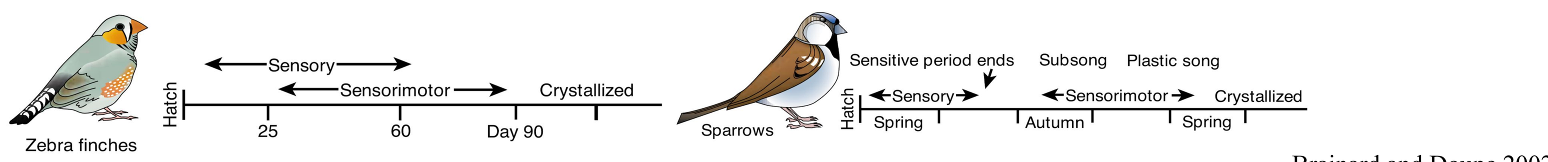
a. Adult zebra finch song

Learning phases:

Sensory phase
Building neural representation of the song.

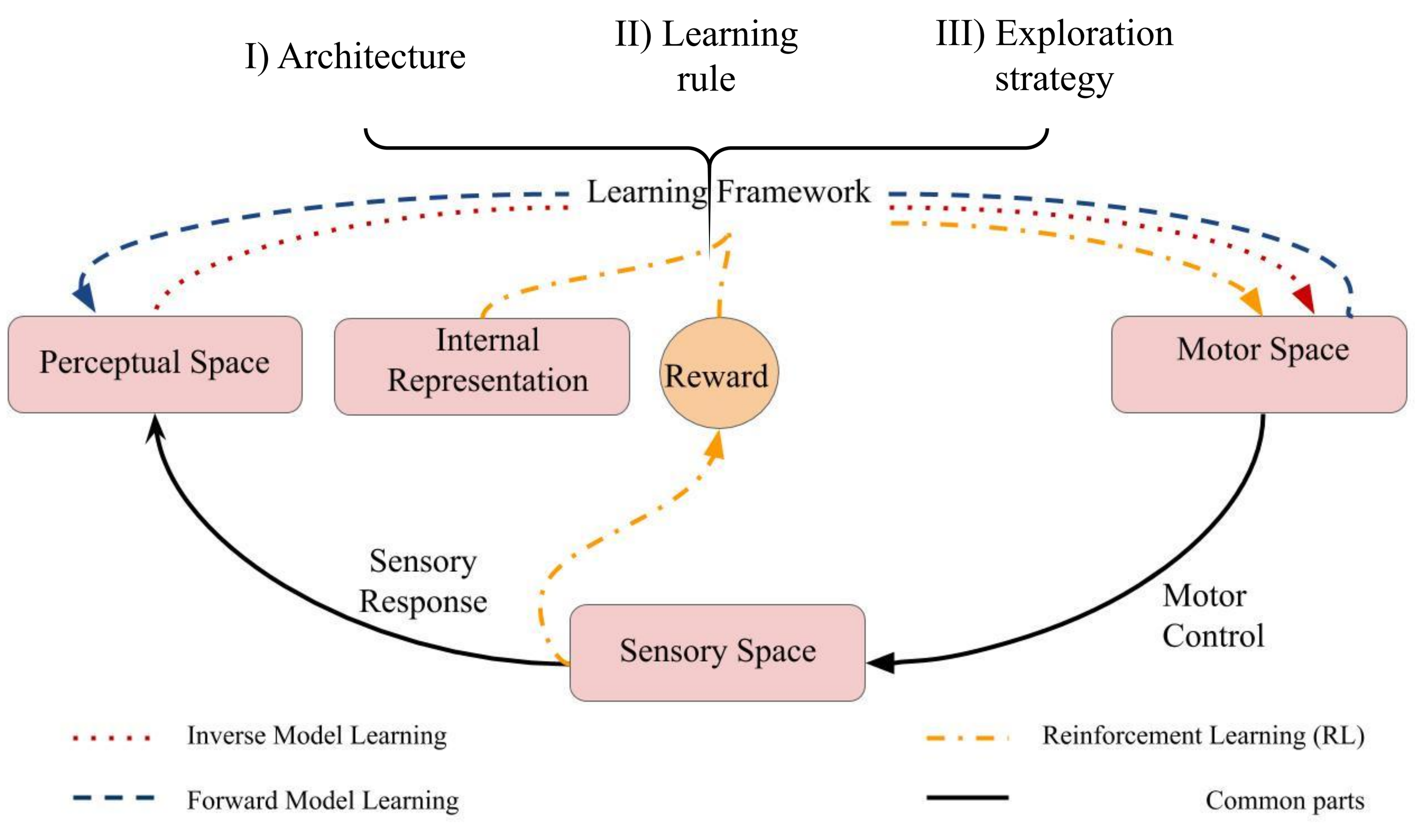
Sensorimotor phase
b. Subsong (babbling).

c. Plastic song (temporally structured).
Crystallization



Brainard and Doupe,2002

SENSORIMOTOR MODEL COMPONENTS [1]

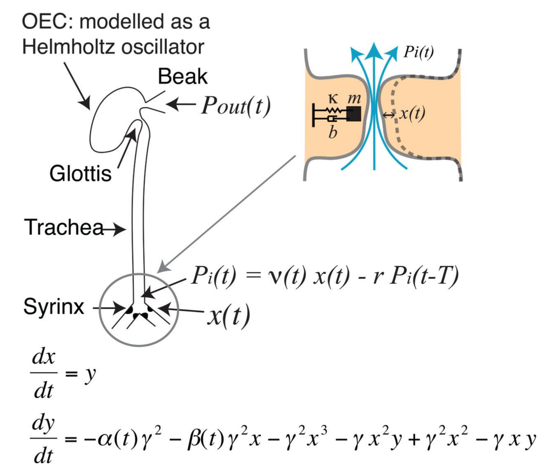


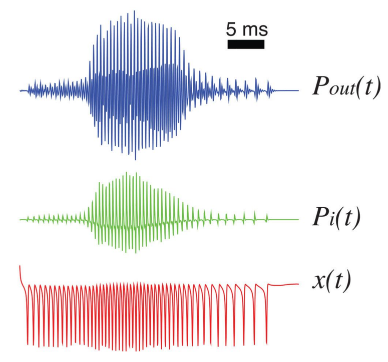
Motor control model

- Respiratory system and vocal organs.
- Anatomical properties and small size of birds make the investigation of vocal fold mechanisms difficult.
- The vocal output is driven by a complex gesture-dependent control scheme, and the brain does not control each motor control parameter independently [2].

Perceptual space

- How the brain encodes sensory stimulus.
- Highly nonlinear dynamics.
- Low dimensional representation of the sensory space.





Amador et al.,2013

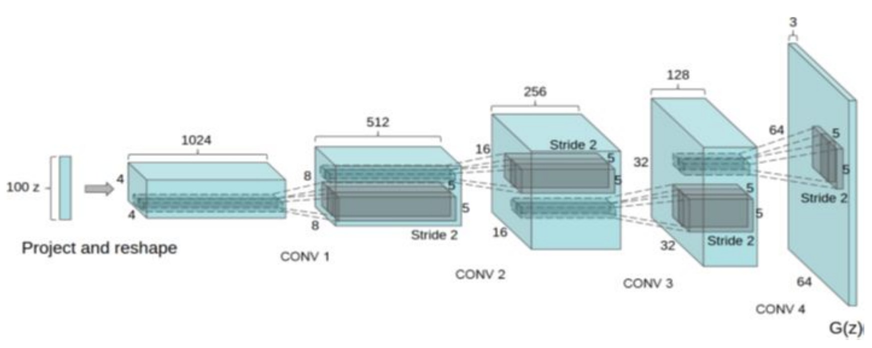
MOTOR CONTROL MODEL

AIM: learn the semantic modes in high-dimensional audio signals, and build a latent space useful for exploration. In addition, have sound production in the model.

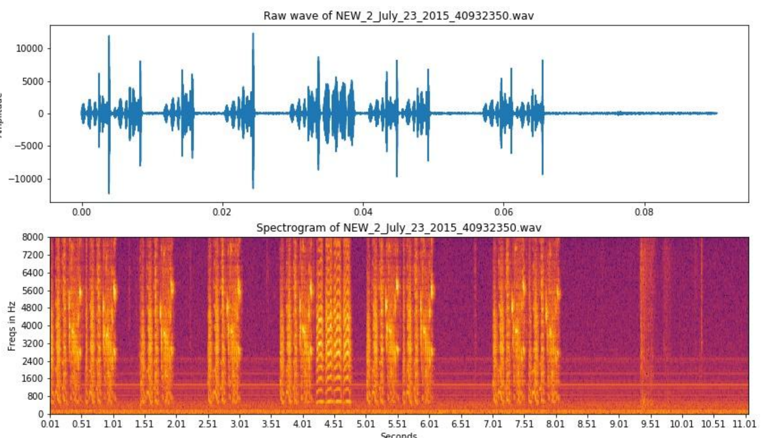
WaveGAN [3]
- Two player minimax game: generator VS discriminator [4].
- Inspired by DCGAN architecture [5].

GENERATOR

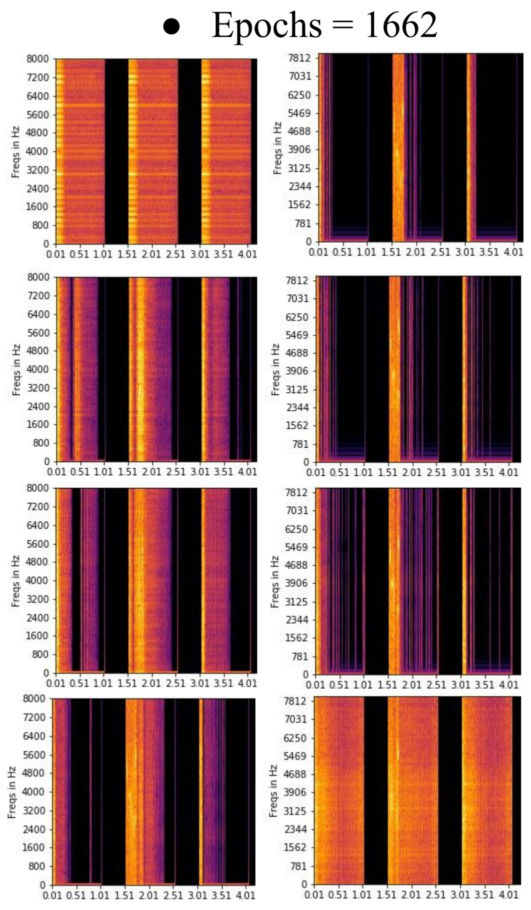
Random input



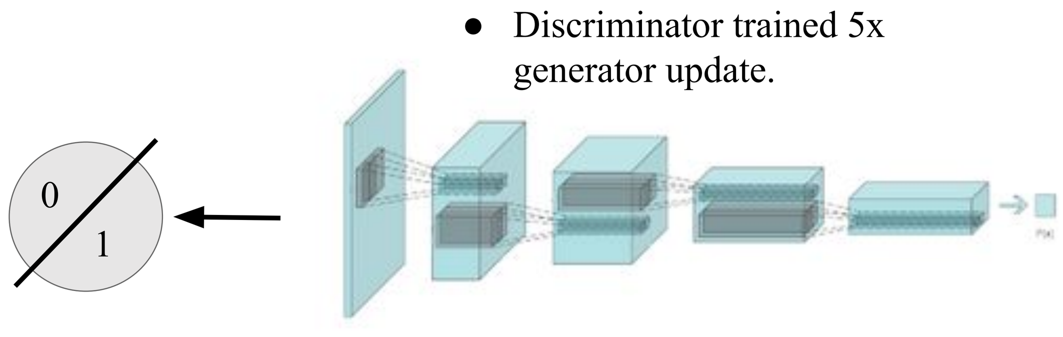
DATASET
- Recordings from an adult zebra finch with sampling rate 44100.
- Downsampled single syllables. N = 4946 syllables.



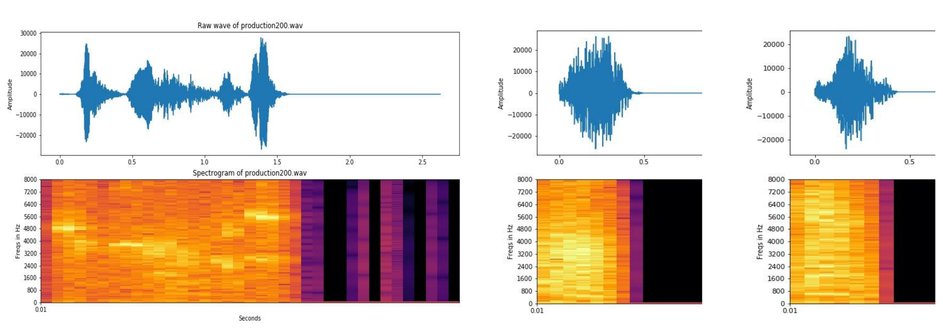
GENERATED SOUND DURING TRAINING
- Batch size = 64
- Epochs = 1662



DISCRIMINATOR
- Discriminator trained 5x generator update.



GENERATED SOUND AFTER TRAINING
- Batch size = 64
- Epochs = 517



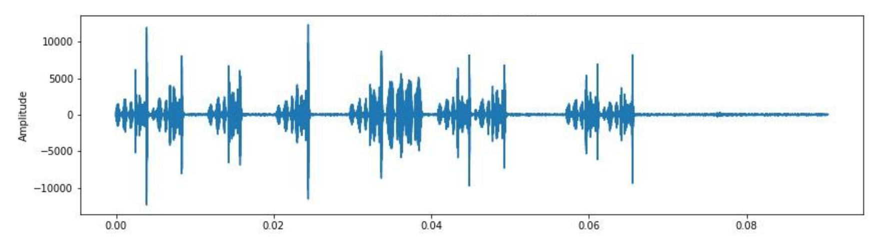
Inception Score (IS) = 1.95 ±0.02

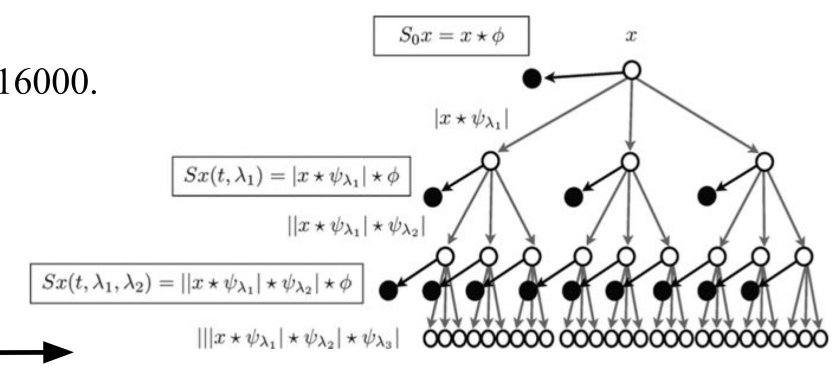
PERCEPTUAL SPACE

AIM: have a lower dimensional representation of the physical acoustic space, which is the sensory space (sound).

Deep scattering transform [6]
- From MFCC coefficients introducing wavelets.
- Scattering coefficients can be seen as a convolutional neural networks.

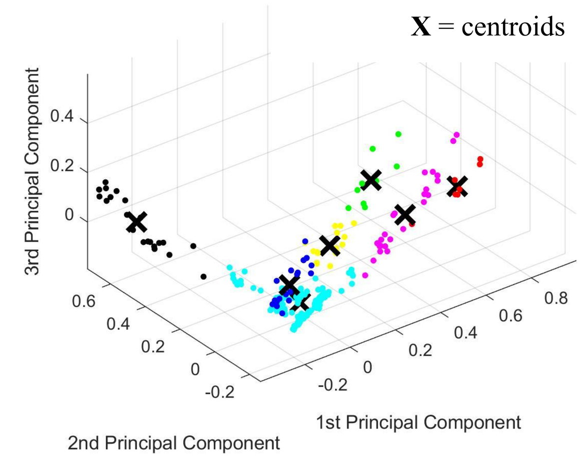
DATASET
- Recordings from an adult zebra finch with sampling rate 16000.



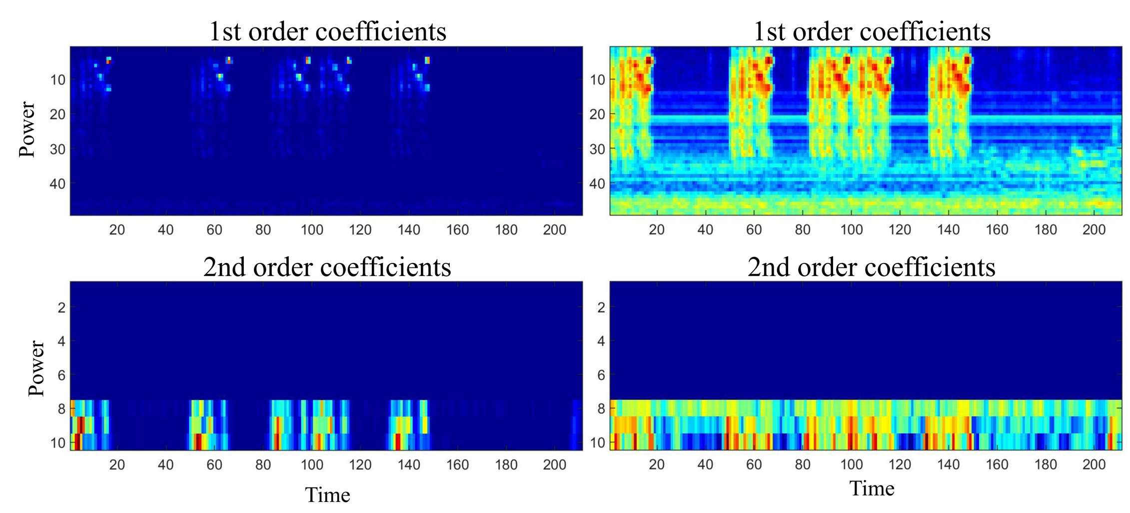


- Averaging window = 800
- 1st and 2nd order coefficients.
- Cell array: elements correspond to layers in the scattering transform.

PCA analysis
- N = 52 syllables.
- PCA analysis.
- k-means algorithm.



Second-order, translation-invariant scattering transform of one-dimensional signals



PERSPECTIVES

Motor control model
- Explore the possibility to use a dynamical system model.
- More exaustive evaluation of the generative modle.

Exploration strategy
- Intrinsic motivation to drive motor exploration.
- Investigate the geometrical properties of latent space generated with the GAN.

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